RISK BASED MINE PLANNING ACCOUNTING PRICE UN-CERTAINITY

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE

REQUIREMENT FOR THE DEGREE OF

BACHELOR OF TECHNOLOGY

IN

MINING ENGINEERING

BY

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DEPARTMENT OF MINING ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY

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National Institute of Technology

Rourkela

CERTIFICATE

This is to certify that the thesis entitled **“Risk based mine planning price uncertainty”** submitted by Sri Manas Ranjan Sethi (Roll No. 108mn019) in partial fulfilment of the requirements for the award of Bachelor of Technology degree in Mining Engineering at the National institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in this thesis has not formed the basis for the award of any Degree or Diploma or similar title of any university or institution.

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CONTENTS

	Page no.
Certificate	i
Acknowledgement	ii
Abstract	iv
List of Figures	v
List of Tables	vi
1. Introduction	1
2. Literature Review	3
3. Methodology	
3.1. Objective	7
3.2. Price forecasting	7
3.3. Problem formulation	9
3.4. Pseudo code for production scheduling	17
4. Case Study	19
5. Results and Discussions	21
6. Conclusion	30
7. Reference	32

ABSTRACT

Production scheduling of an open pit mine is a process of assigning mining blocks to different production periods so that the total profit from the mine can be maximized over the life of the mine. Long term mine plans are based on a single price value, but by the time development is put in place, production plan may have been proved wrong and production plan may not achieve the desired objective. So, the production plan is changed again which results in inefficient use of capital with low returns to investors.

The proposed stochastic version of the conventional (deterministic) network flow algorithm is based on the use of multiple simulated realizations of metal selling price uncertainties. In comparison to the conventional pit optimization methods, where only one estimated or average type model of the deposit are used, the use of multiple scenario results in the ability to generate greater risk profiles in terms of metal price for pit design and production scheduling for greater profit making throughout the entire life of mine.

The method is applied for optimizing the annual production scheduling at an Iron ore mine, and compared against a traditional scheduling method using the traditional single "average type" assessment of the mineral resources. In the case study presented here in, the schedule generated using the proposed SIP model resulted in approximately 5% higher NPV than the schedule derived from the traditional approach.

List Of Figures

Fig No.	Fig Title	Page No.
3.1	Block showing slope constraint	10
3. 2	Ore body extraction sequence	11
3. 3	Blocks with BEV values	13
3.4	Blocks with positive and negative BEV values are connected to source and sink	14
3.5	Source and sink are connected to respective blocks of different simulation	15
3.6	Combination of all simulated blocks	16
3.7	Ultimate Pit of different simulation and of combined block	16
3.8	Stochastic ore body model	17
5.1	Iron ore price chart: 1982-2011	22
5.2	Normalized price values	23
5.3	Experimental variogram	23
5.4	Fitted variogram	24
5.5	Experimental variogram of iron ore price	25
5.6	Predicted iron ore price for 10 years with 10 simulation for each year.	25
5.7	Production chart	26
5.8	a) Ultimate pit in XY direction b) Ultimate pit in YZ direction 3-D view of pit	27
5.9	c) Net Present value chart	28
5.10	NPV chart for both deterministic and for stochastic average	29

List Of Tables

Table No.	Table Title	Page no.
5. 1	Variogram fitting data	22
5.2	Production scheduling for different year along with percentage deviation from target	25

CHAPTER 1

INTRODUCTION

1. INTRODUCTION

Mine production scheduling is an optimization process which assigns the extraction sequence of a mining block under certain constraints such that it maximizes the net profit. The mine production scheduling is a large scale mixed integer programming problem, is a NP hard problem, is difficult to solve with commercial solvers. In open pit mine planning and production scheduling, Lerchs- Grossmann algorithm with heuristic as well as network flow algorithm are industry standard. The traditional process to generate mining schedule is a three step process. First, the ultimate pit is obtained by implementing the Lerchs-Grossman (L-G) (Whittle 1999). In the second step, the ultimate pit is sub-divided into a series of nested pits, or pushbacks by a different parameterization algorithm, (Seymour 1995; Bongarcon and Guibal 1983). Lastly, an MIP, or heuristic algorithm, is applied on the series of small pits to obtain the production scheduling (Ramazan and Dimitrakopoulos 2007). Another algorithm to solve the large mine scheduling problem is by the aggregation of blocks to reduce the number of integer variables (Boland et al. 2009). Although the aggregation algorithm provides an optimal solution, it has two major limitations. First, for scheduling a large size deposit, the aggregation approach is also impossible to solve with presently available commercial solvers. Secondly, an aggregation will change the economic values of the blocks, which ultimately changes the entire problem into something far different from the original problem.

Long term mine plans are based on a single price value, but by the time development is put in place, production plan may not achieve the desired objective. At this point the common reaction to this situation is to create a new revised long term plan and spend more capital, only to find out at the later time but by that time metal price may have changed again (increased or decrease) which results in an inefficient use of capital with low returns to the investors with lower net present value. From this, it is concluded that it is necessary and important to incorporate price uncertainty while production planning which will result in optimized production scheduling throughout the life of mine.

This thesis focuses on the production scheduling of open pit mine taking selling price uncertainty of metal.

CHAPTER-2

LITERATURE REVIEW

2. LITERATURE REVIEW

2.1. Mine production scheduling

From last three decades, several attempts were made to integrate uncertainty into mine planning and production scheduling. In order to incorporate risk in mine planning and production scheduling, a set of equally probable ore body models are required. The set of equi-probable models are able to incorporate uncertainty into the formulation of the production scheduling problem (Dimitrakopoulos et al., 2002). Ravenscroft (1992) suggested a probabilistic approach to generate production schedules for the entire life-of-mine. Godoy (2003) proposes a stochastic approach to manage geological risk in best possible way over the life of the mine production scheduling and reports a 26% improvement from the use of stochastic optimization based on simulated annealing. Dimitrakopoulos et al (2007) demonstrated a model using the concepts of upside/downside potential to include grade uncertainty in the long-term production schedule. Several mine designs for a set of simulated ore bodies are obtained and a final one selected by considering the one with a minimum downside or maximum upside potential. Dimitrakopoulos and Ramazan (2004) developed a mathematical programming formulation to minimizing deviations form production targets by considering a probabilistic approach. The new concept of geological discounted rate is introduced and produces a decreasing unit cost for deviation of target over the life of mine. Ramazan and Dimitrakopoulos (2007; 2008) propose an approach that accounts for all available realizations of the ore body simultaneously in a stochastic integer programming formulation. Their formulation has objectives the maximization of net present value and minimization of deviation from production targets. Different penalties may be defined for deviations of different targets. Mine plans are updated regularly as new ore zones are added and older reserves are depleted. However, this work is subjected to rapid obsolescence as metal prices changes over time. If mine prices go up, there is a requirement to mine more and faster, producing a strain on the existing infrastructure. The operation may run out of supply if the development cannot keep up with extra demand. If the prices drop, the economically extractable ore body shrinks and the existing development does not suffice to meet the production targets.

Fig-1 depicts the price of iron ore over past 30 years i.e. 1982-2011. From figure-1, it is certain that metal price variation is very uncertain, which affects mine planning considerably. Hence it is concluded that metal price uncertainty plays an important role and must be incorporated in mine planning and production scheduling for higher profit making.

2.2. Future metal price forecasting

Metal price behaviour is predominantly associated with trend determination and component analysis. Philips and Edwards (1976) derived an inverse relationship between ore grade and metal price with ore grade falling over time. Lee (1976) showed that in terms of real or constant prices, price trends in different markets manifest similar structural characteristics. Wood et al. (1977) using moving average of deflated and converted London metal Exchange price series determined an upward trending curve for copper. Petersen and Maxwell (1979) suggested a general inverse relationship between mineral prices and production with cost a controlling factor. They determined that three basic price trends were followed over time falling, stale and rising. Slade (1982a, 1982b) emphasized the relationship of scarcity and investment with real prices of natural resource commodities. She found increasing scarcity reflected in concave quadratic price trends and cycles seen were an effect of the timing of investment in the industry.

Different methods have been suggested and tried for prediction of metal prices. O' leary and Butler (1978) used Fourier analysis and power Spectrum determination on real copper prices to predict the future prices. Real copper price differences and random walk model were used to generate future prices in the study done by Rudenno (1982)

It has been suggested (Journel and Huijbregts 1978) that metal price time series are one dimensional regionalized random variables. This implies that geostatistical methods could be used to estimate metal prices. Faulkner (1988) has successfully predicted the metal prices using Geostatistics. The most important properties of Geostatistical simulations are, producing a group of images which shows range a possible events, calculating probable percentage of happening and also determining the risk in each step of process. From the above discussion it can be conclude that Sequential Gaussian Simulation (SGC) can be used for prediction of metal price series.

CHAPTER-3

METHOHODOLOGY

3. METHODOLOGY

3.1. Objective:

Optimization of production scheduling taking metal price uncertainty.

- Price forecasting using sequential Gaussian simulation.
- Production scheduling taking uncertainty of the forecasted price.
- A comparative study of the proposed method with production scheduling using deterministic approach.

3.2. Price forecasting

The price forecasting is done using the Sequential Gaussian simulation.

3.2.1. Sequential Gaussian Simulation

Sequential Gaussian simulation algorithm which simulates nodes after each other sequentially, subsequently using simulated values as a conditioning data. In sequential Gaussian simulation standard Gaussian values are used, transforming the data into Gaussian space. The basic steps sequential Gaussian simulations are (Deustch, C.V., journel, 1992)

1. Calculate the histogram of raw data and other statistical parameters
2. Transform the data into Gaussian space.
3. Calculate the model variogram of Gaussian data.
4. Define a grid.
5. Choose a random path.
6. Krige a value at each nodes from all other values (known and simulated) and define Gaussian.
7. Draw a random value from Gaussian distribution which is known as simulated value
8. Simulate other node sequentially.
9. Back transform simulated values.
10. To generate other realization, repeat step 1 to step 9.

Variogram of transformed data are calculated and modelled. It is necessary to define a grid for simulation and a random path to asses grid nodes. According to the kriging mean and variance of a Gaussian probability distribution is determined in each node. For estimating at each node it's necessary to choose a random path. A random value which is drawn from Gaussian probability distribution is known as simulated value at each node.

The semi-variogram in step-3 of SGS is calculated using the following procedure.

3.2.2. Semi-Variogram

The semi variogram is the mean squared difference in metal price for various time separations (lags) of the prices. If the semi-variogram function is conditionally positive definite its behaviour at infinity is such that it increases more slowly at infinity than does the squared time separation. If the semi-variogram function increases at least as rapidly as the time separation squared for large time separation it is incompatible with the intrinsic hypothesis. Therefore there is a trend or a drift in the mean, variance, semi-variogram or auto-covariance (Journel and Huijbregts 1978).

If the hypothesis of the second-order stationary or quasi-stationary is satisfied, the model of the semi-variogram increases continuously with some degree of regularity to a ‘sill’. For second-order stationary the ‘sill’ is equal to the variance of the metal prices minus the nugget effect. For quasi-stationary the’sill’ is equal to a positive, finite variance minus the’ nugget effect’. The time separation or ‘lag’ at which the increasing semi-variogram function interacts the ‘sill’ is known as the ‘range’. From this point of interaction the model is constant and equals the ‘sill’and the auto covariance is greater than or equal to zero.

If only the intrinsic or quasi-intrinsic hypothesis is satisfied and the semi-variogram function is conditionally positive definite, the model will continuously increase as the size of the time separation increases. The variance of the metal prices is dependent on the time separation and not any point in time. Therefore no ‘sill’ exists in the semi-variogram.

3.2.2.1.Semi- Variogram Model

In this study semi-variogram is calculated using the spherical model which can be formulated as follows.

$$\boldsymbol{\Upsilon}\ \mathbf{(t) = C}\ [\frac{\boldsymbol{3t}}{\boldsymbol{2a}} - \frac{\boldsymbol{t^3}}{\boldsymbol{2a^3}}] + \mathbf{C_0}$$

Where; γ(t) = the semi-variogram function at time separation t.

C = the ‘sill’, a positive variance or variance of the metal prices minus the ‘nugget effect’.

a = the ‘range’ of continuity and regularity, the ‘lag’ at which the semi-variogram reaches a ‘sill’.

t = the time separation or ‘lag’

C_0 = the nugget effect whose value is equal to the semi-variogram function at ‘lag’ 0.

3.2.3. Methodology for price forecasting

All the price values are transferred to its normalized form using Gaussian distribution. Then sequential Gaussian simulation is performed. Then an experimental semi-variogram was calculated from metal price series. If the experimental semi-variogram did not exhibit a "Pure nugget effect" a theoretical semi variogram function was fitted. A fitted model indicated structural correlation between prices in the time series and it was then used to krige future prices. These future prices were compared to deflated known prices and future prices are predicted from a simple random walk based on the probability of past price data.

3.3. Conceptual formulation of the problem

This section conceptually presents method applied in this paper.

3.3.1. Formulation of the Objective function:

Let Xt is a mining block of an open pit mine, where $Xt \in X$ and X is set of all blocks in the deposit. Mine production scheduling can be formulated as mixed integer programing with time indexed binary variables $X_{i,t}$, $i \in N$, $t = \{1, \ldots, T\}$ which are defined by $Xi,t = 1$ if mining block is extracted at time t, and $X_{i,t} = 0$ otherwise. This leads to the following stochastic integer programming formulation

$$Z = \text{Max}\ \frac{1}{S}\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{s=1}^{S}\frac{Ci^{s}}{(1+r)^{t}}Xit \qquad (1)$$

Subjected **to**

$$X_{i,t} - X_{j,t} \leq 0, \qquad j \in \Gamma i,\ i \in N, t \in T \qquad (2)$$

$$\sum_{t=1}^{T}\sum_{i=1}^{N} Xi, t = 1 \qquad (3)$$

$$X_{i,t} \in \{0, 1\}, i \in N, t \in T \qquad (4)$$

$$\sum_{i=1}^{N} a_i^t x_{i,t} \leq b_1^t \qquad (5)$$

Where Γi is the set of successor nodes i; Ci is the set of economic value of block i; n is the number of blocks in the model; a_i^t is the amount of tonnage obtained from a block X_i. $b^t{}_i$ is the maximum mining capacity at a time; T is the total number of production period; r is the mining rate. Equation (2), (3), (4) and (5) are different constraints applied to the main objective function i.e. equation (1).

Equation (2) describes the slope constraint of extraction i.e. for extraction of a block; its overlying blocks must be extracted before, which is demonstrated in fig.3.1. In fig.3.1 , for extraction of block C5 following a slope constraint of 45 degree, C1, C2 and C3 blocks are extracted first.

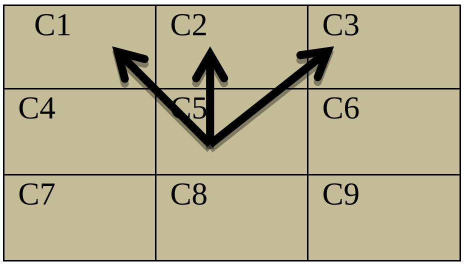
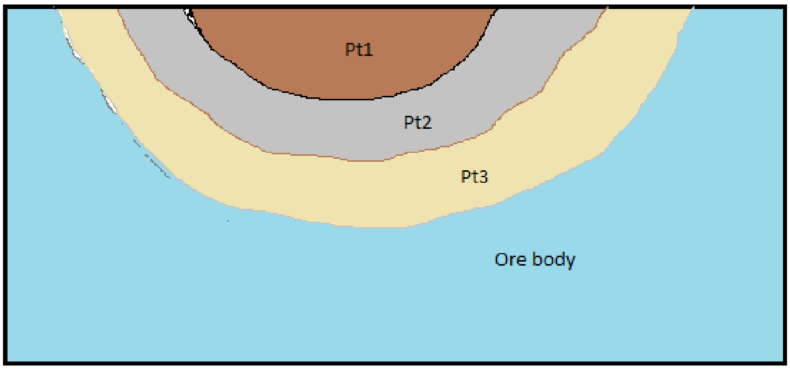


Fig. 3.1: block showing slope constraint

Equation (3) describes the reserve constraint i.e. a particular bock is extracted only once in all simulated ore body. Equation (4) describes the binary constraint i.e. a block is either extracted or it hasn't been extracted. For this, we take the value 0 for x if the block has been extracted and the value 1 if the block hasn't been extracted. Equation (5) describes the mining constraint i.e. mining production cannot exceed a fixed tonnage value because of limitation of technology, machinery available etc.

Solving this stochastic integer programming (SIP) formulation for large scale deposit is computationally prohibitive. An approximation technique is proposed to solve the large scale SIP. The SIP is solved by solving a series of graph closure with resource constraints formulation. If P is the total number of blocks in the ore body model, the graph closure with resource constraints is formulated and solved to obtain the production scheduling for the time period t. If Pt is the number of blocks assigned to be extracted during the time period t , then the number of blocks remain in the ore body model to be scheduled in the remaining period are $P' = P - Pt$, the remaining ore body model then be used to formulate with resource constraint for the period $t+1$. This is demonstrated in figure.3.2. When 1st year production (Pt1) is produced, The SIP is applied to rest part of ore body excluding Pt1, i.e. now the ore body becomes P' = P – Pt1. This procedure will continue until no blocks are left in the ore body model to optimally assign to a particular period of extraction.



Pt1,Pt2 and Pt3 are production in 1st,2nd and 3rd year respectively

Fig.3.2: Ore body extraction sequence

3.3.2. Approximation algorithm for year wise production

The graph closure with resource constraints problem formulation of the open pit scheduling for period *t* aims to maximize *Pt*, after respecting different constraints at a period *t* and can be formulated as which can be solved by minimum cut method.

$$Pt = \text{Max}\ \frac{1}{S}\sum_{i=1}^{N}\sum_{s=1}^{S} Ci^{s} x_i \qquad (7)$$

Subjected to

$$X_i - X_j \leq 0,\quad j \in \Gamma i,\ i \in N, \qquad (8)$$

$$X_i \in \{0, 1\},\ i \in N \qquad (9)$$

$$\sum_{i=1}^{N} a_i x_i \leq b_1 \qquad (10)$$

Where

Ci = block economic value

b1 = production target for 1 year

a1 = amount of tonnage obtained from block Xi.

3.3.3. Block economic value calculation

Block economic value *Ci* can be calculated using the formula:

$$c_i = t_i \times G_i \times R_i \times P_i - t_i \times C_p - T_i \times C_m$$

Where

c_i = Block economic value, $

t_i = Tonnes of ore in the block *i*

G_i = Grade, unit/tonne

R_i = Recovery

P_i = Unit price, $/unit

C_p = Processing cost, $/tonne

T_i = Total amount of rock (ore and waste) in the block *i*

C_m= Mining cost, $/tonne

As price is different for different realization so, different block economic value (BEV) is calculated for the same block.

3.3.4. Minimum cut / Maximum flow method

The network flow algorithm (Ahuja and Orlin, 1989), is an algorithm for designing an open pit using the maximum flow (minimum cut of arcs) between nodes, under the context of graph closure (Picard, 1976). The nodes are the blocks in the mining blocks in the ore body model. Arcs are constrained between the nodes; these arcs all bear a capacity. The goal of the maximum flow algorithm is to cut the arcs which carry the least capacity (Goldberg, 1988; Gallo et al., 1989; Faaland et al, 1990).

In the network flow algorithm, all mining blocks are seen as nodes; they are the data points in the 3 dimensional space. These nodes are connected to each other by capacity arcs. In order to run the algorithm, a source and sink node are established. The source and sink nodes are data points created outside the dataset. The arcs in the directed graph $G = (V, A)$ where a node in the graph represents a block in the ore body model, have a capacity based on the block economic value; the source node is connected by an arc to the positive BEV, ore, and the sink node to a negative BEV, waste (Hoochbaum and Chen, 2000; Hochbaum, 2001, 2003, 2004 and 2008). Arcs are the connection between nodes, for example between blocks that are on top of each other or have a connection to the source and sink. In addition to the arcs to the source and sink based on BEV, these are arcs between blocks; these are the slope constraints and have a unlimited capacity. This is because overlying blocks have to be mined before extraction of target block. Since there is no direct path between source node to the sink node, a cut has to be chosen to design the open pit. This cut will be a minimum cut so that the set of capacity arcs which will be cut bear the minimum possible capacity; in other words the sum of capacity of arcs is minimal. This means there is a minimal amount of ore outside the pit and there is a minimal amount of waste in the ore pit. (the minimum cut graph).

The limitation of this method is that it only looks at differences, and so distributions, of single blocks while the local uncertainty is uncertain of a neighbourhood, and thus contains multiple blocks. By considering the uncertainty for each single block separately only a part of the local uncertainty is addressed.

A two dimensional block is shown in fig.3.3 for demonstration where positive values are given to ore blocks and negative values are given to waste blocks. By making connection for directed graph following different constraints the resultant graph is shown in figure3.4. In fig-4 slope constraint of 45 degree is maintained.

3	6	-1	3	-1
-2	7	-1	5	-1
-4	9	5	-6	-3

Fig: 3.3-: Blocks with BEV values

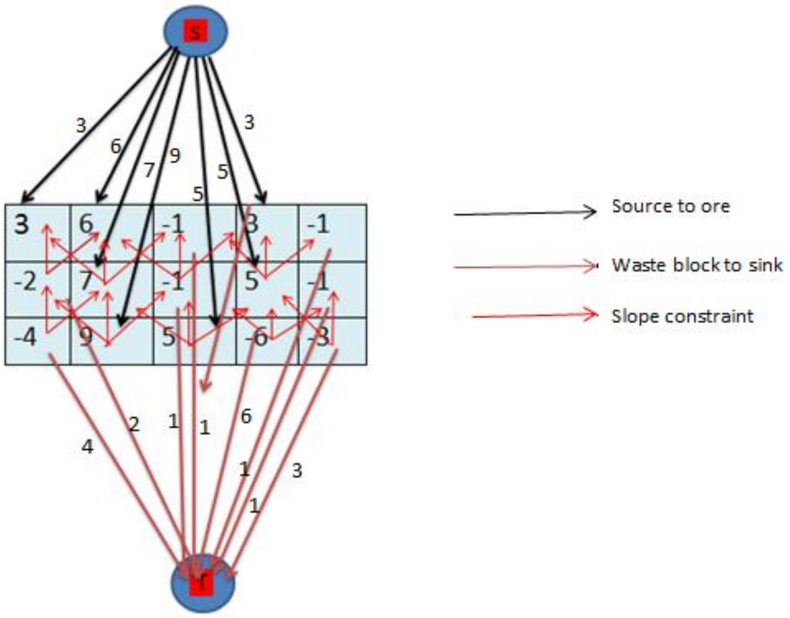


Fig.3.4- blocks with positive and negative BEV values are connected to source and sink

3.3.4.1.A Stochastic Network Flow Algorithm

A stochastic version of the network flow algorithm (SNFA) uncertainty (Chatarjee, S., Dimitrakopoulos, R, 2010) in the BEV is used to account for the geological risk in open pit design (Meagher et al, 2009; Meagher, 2011). Simulated equally probable models of an ore body are used by SNFA to manage uncertainty (Dimitrakopoulos et al. 2002; Leite and Dimitrakopoulos, 2007; Leite, 2008; Dimitrakopoulos and Ramazan, 2008). Instead of working with a precise and possible wrong model, the calculation are done on a set of scenarios (Meagher et al., 2009, 2010; Chatarjee et al., 2009, 2010). This maximizes the net present value (NPV) for an open pit, given the uncertainty from limited data and ore body models.

The method works as follows; when the simulations are run, the economic block value of each block in each simulation is calculated. Then, the blocks with a negative BEV will be connected to a sink which is same for all simulations (one single sink node). The same is done with blocks having positive BEV value; these are connected to a single source node and the precedence constraints have to be maintained. In addition, blocks that have the same location in the grid (x, y, z) will have infinite number of capacity arcs between them. The new constraint exists because the same blocks in the grid have to be either inside or outside the pit for each of the simulations since only one pit is being designed.

The next step of the algorithm is to merge the blocks at the same position to one block (node), which has maximum one arc from the source node and one arc to the sink node. Where these arcs have the capacity of the sum of the capacity of the arc at the same location in the single simulation (Meagher et al., 2010). This will result a single graph or matrix (figure:3.5) which makes the process less computationally demanding, because the number of node is massively reduced and only one minimum cut algorithm is needed. When more simulations are added to the process, the capacity of the arcs will noticeably increase.

For example there are 3 different simulations, all of these are equal probable to occur (figure no: 3.5) thus when network flow algorithm is used three different ultimate pit designs will be generated (Fig no: 3. 6). These ultimate pits could all be the actual ultimate pit. By using a stochastic data input, thus multiple scenarios, an ultimate pit can be generated taking this price uncertainty in to account, as shown in figure. Similarly, combined matrixes of different simulations are obtained for different year of production as shown in fig-3.8. Then the same procedure of minimum cut is followed to find the ultimate pit by incorporating price uncertainty throughout the life of the mine.

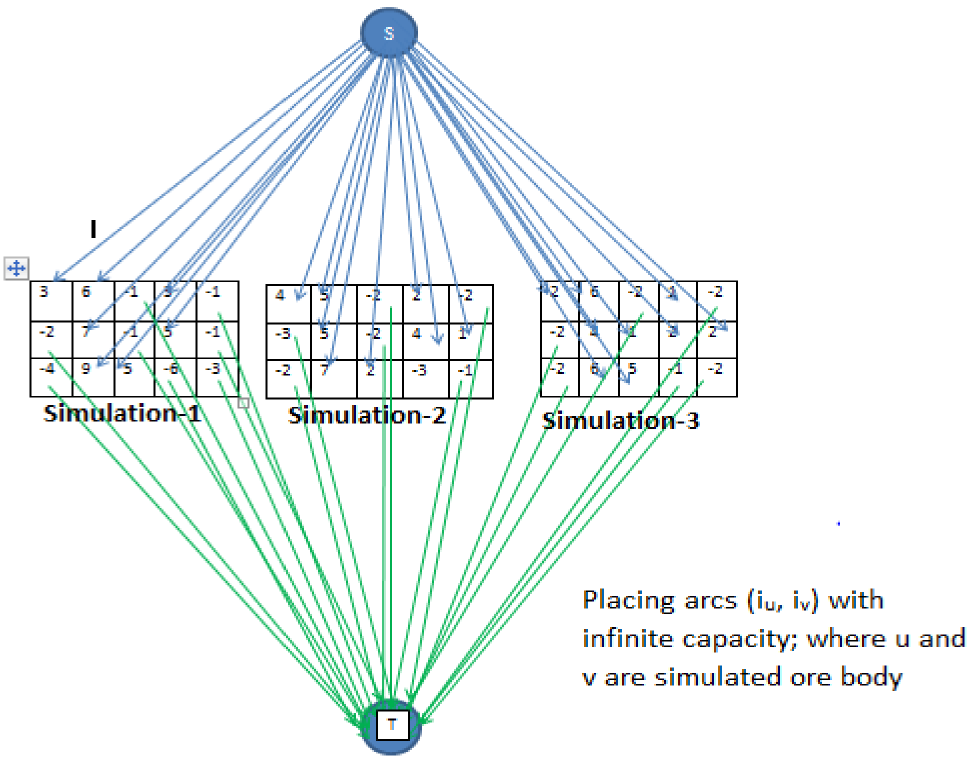


Fig: 3. 5- Source and sink are connected to respective blocks of different simulation

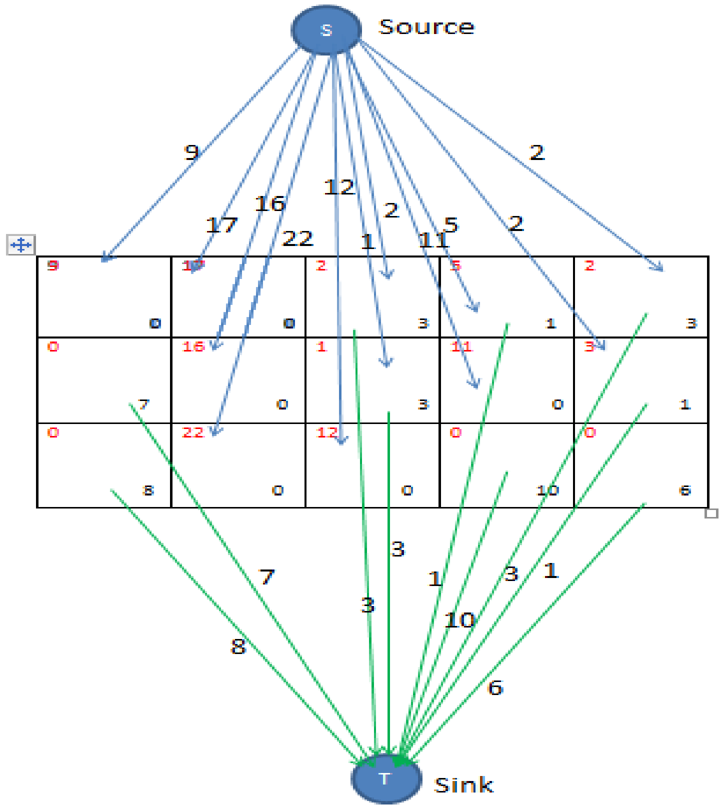


Fig: 3. 6 - Combination of all simulated blocks

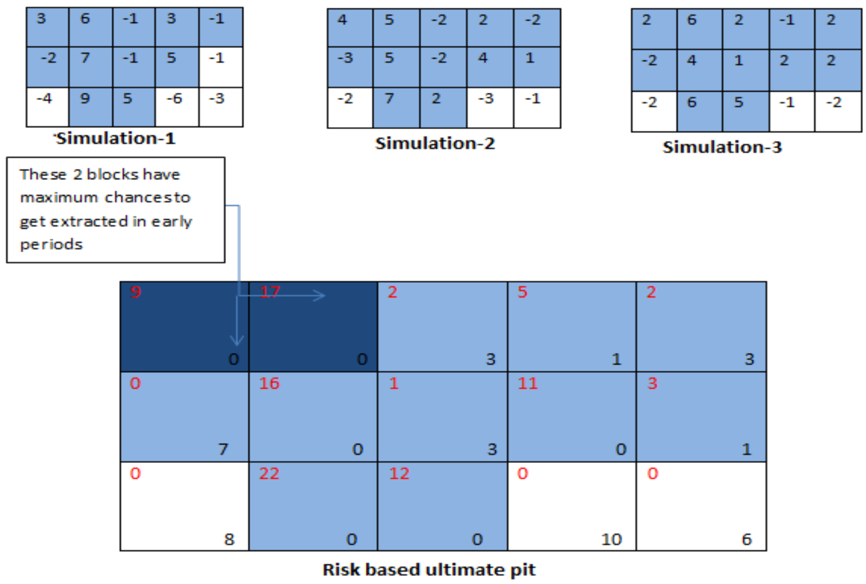
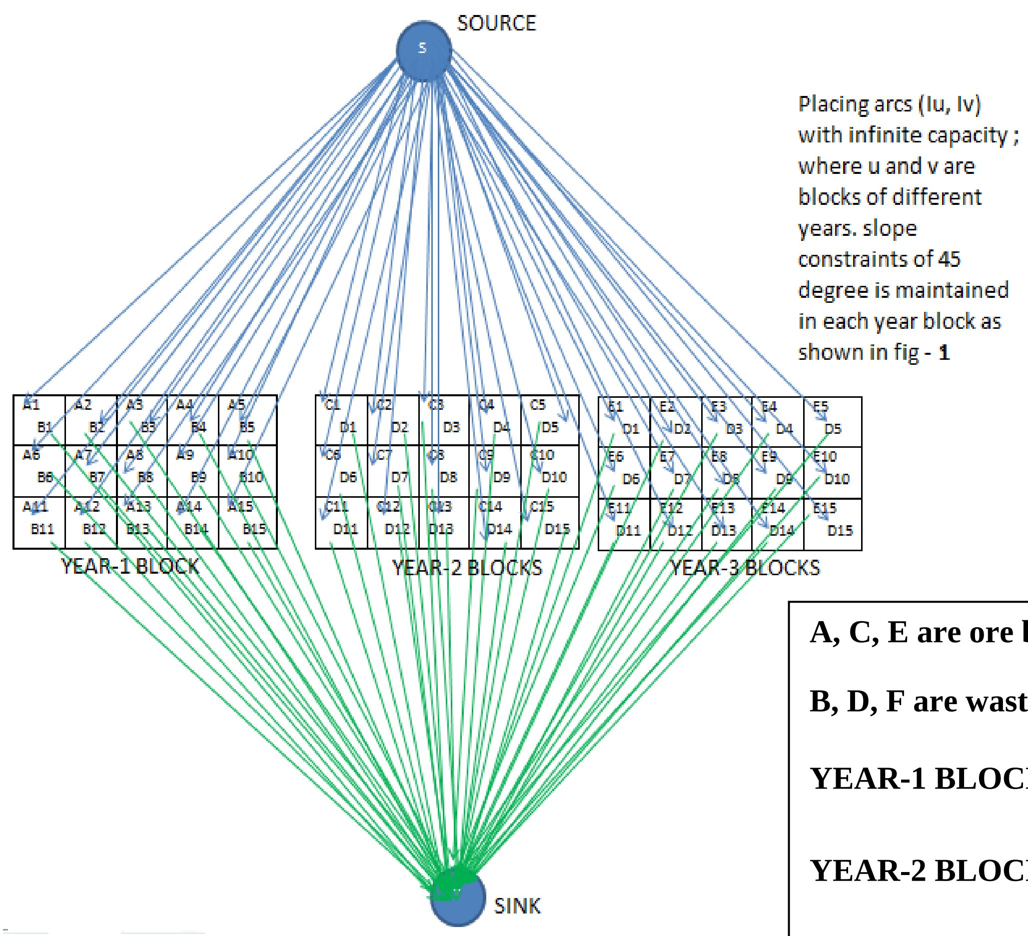


Fig: 3.7 - Ultimate Pit of different simulation and of combined block.



A, C, E are ore blocks

B, D, F are waste blocks

YEAR-1 BLOCK = $\frac{BEV}{(1+r)^1}$

YEAR-2 BLOCK = $\frac{BEV}{(1+r)^2}$

YEAR-3 BLOCK = $\frac{BEV}{(1+r)^3}$

Where, BEV = block economic value

Fig: 3.8- stochastic ore body model

3.4. PSEUDO CODE FOR PRODUCTION SHEDULING

The following pseudo code is followed for getting year wise production

<u>Steps</u>

1. Define a variable, say λ such that $0 < \lambda. < 1$.
2. Initialize $\lambda = 0$.
3. Set ore production and best production equal to zero at $\lambda = 0$.
4. Increase λ by small value $\Delta\lambda$. . i. e. $\lambda. = \lambda + \Delta\lambda$
5. Calculate ore production = solution of network flow (λ).
6. If (ore- production < target production)

Update value of λ by Δλ i.e. λ. = λ +Δλ

7. Go to step 5.
8. Do step 2 to 7 for *t*=1 to *T*.
9. End.

CHAPTER- 4

CASE STUDY

4. CASE STUDY

The study was carried out on an iron ore mine situated in the south-eastern part of India. The deposit lies between latitude $18^{0}41^{'}$ and $18^{0}42^{'}$, and longitude $81^{0}42^{'}$ and $81^{0}12^{'}30^{''}$. This is a hilly deposit with highly undulating ground level. The highest point of the deposit is 1269 m above the mean sea level (MSL) and the lowest point, up to which mineralization found during the investigation, is at 950 m reduced level. Most of the area of the deposit is covered by green vegetation. The area is drained by seasonal nallahs which are flowing both the sides of the deposit. The geological study of the deposit revealed that this iron ore deposit was formed during the Precambrian age. This series of ore consists of iron ore, unenriched banded iron formation rocks (Banded Hematite quartzite), shale, tuff and quartzite. The major iron ore bodies occur along the top of the range and generally at the bottom of the underlying shale. The deposit is situated in the southern ridge of the range. There are numbers of folds, faults present in the mine which indicates that the deposit is highly disturbed in nature. There were 77 borehole data available from the mine for conducting this study. The boreholes are located in a grid pattern; however, the spacing of the boreholes varies from 200-250 meters. The average length of the boreholes is about 100 meters. . The mine has seven different lithology namely Steel Gray Hematite (SGH) Blue hematite (BH), Laminated Hematite (LH), Laterite (L), Blue Dust (BD), Shale (SHL) and Banded Hematite Quartzite (BHQ). Most of the high grade iron ore is associated with still gray, blue and laminated hematite. The average depth of the mine is 160 m. The core samples are composited in 5 m composite length. The deposit is estimated using ordinary kriging method (Chatarjee, 2006). The estimated block size is 50 m x 50 m x 10 m.

CHAPTER-5

RESULTS AND DISCUSSIONS

5. RESULTS AND DISCUSSIONS

5.1. Price Forecasting

Price forecasting is done following the procedure of sequential Gaussian simulation, as described in the methodology section. Past Iron ore monthly price (1982-2011) chart is collected from Index mundi commodity price and is plotted as shown in figure 5.1.

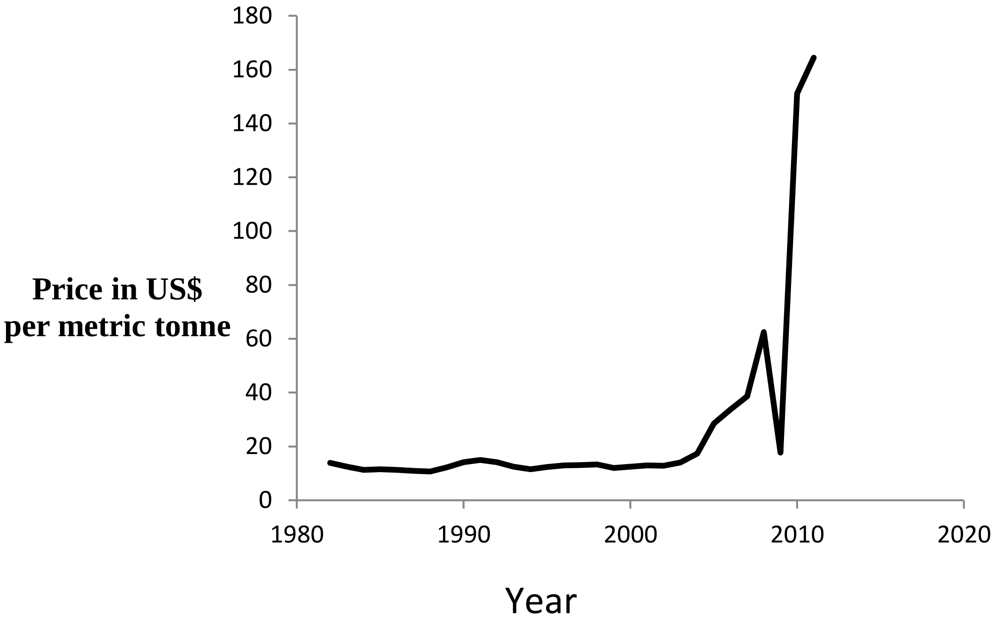


Fig: 5.1 -Iron ore price chart: 1982-2011
Source: Index Mundi commodity price
www.indexmundi.com/commodities/?commodity=iron-ore&months=360

The price values are then transferred to standard Gaussian space by normalizing the price values and the normalized chart is shown in fig-5.2. Then an experimental variogram was calculated from the normalized price data as shown in fig-5.3 and again the fitted with a spherical model as shown in fig-5.4.

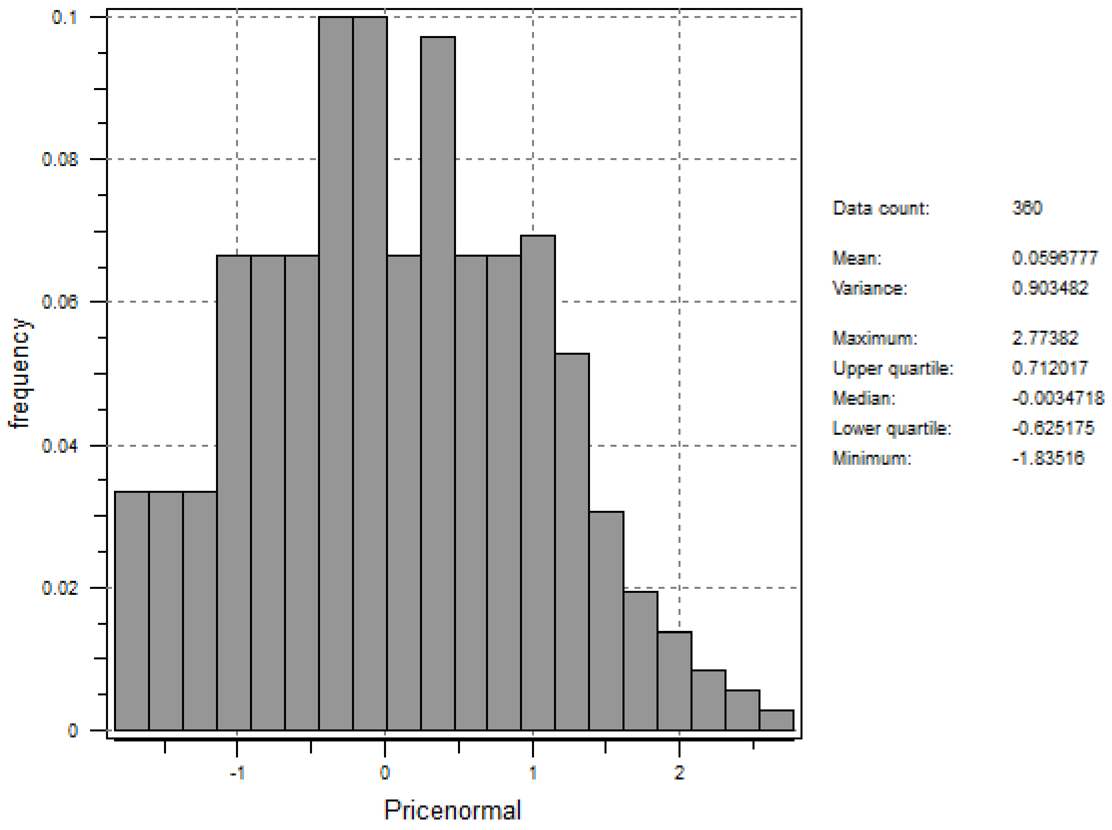


Fig-5.2:- Normalized price values

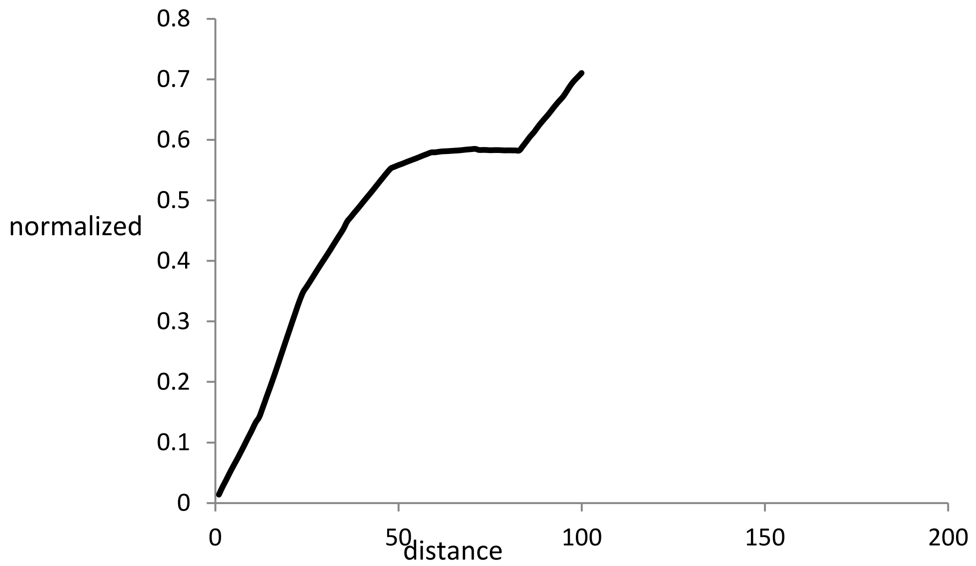


Fig-5.3:-Experimental variogram

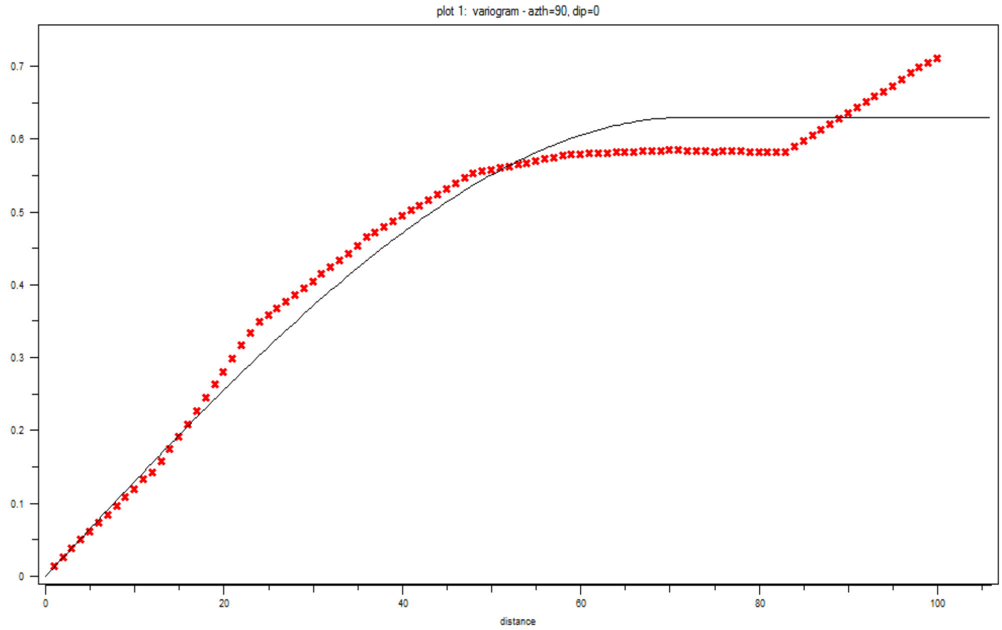


Fig-5.4:-Fitted variogram

Table-5.1: Variogram fitting data

Nugget	No of structure	Sill	Type	Max	Med	Min
0	1	0.63	Spherical	100	70	27

A grid is defined for estimation of next 10 year price i.e., from 2012-2021. Then simulation is done from the Gaussian distribution at the grid. For the present case study 100 realizations is done for each simulation. The experimental variogram of normalized price and normalized price including the simulated price are shown in fig: 5.5. From fig-5.5 it concluded that the estimated results fit well with the past results. Price uncertaity is presented in figure:5.6 by taking 10 realization for forecasted price of each year.

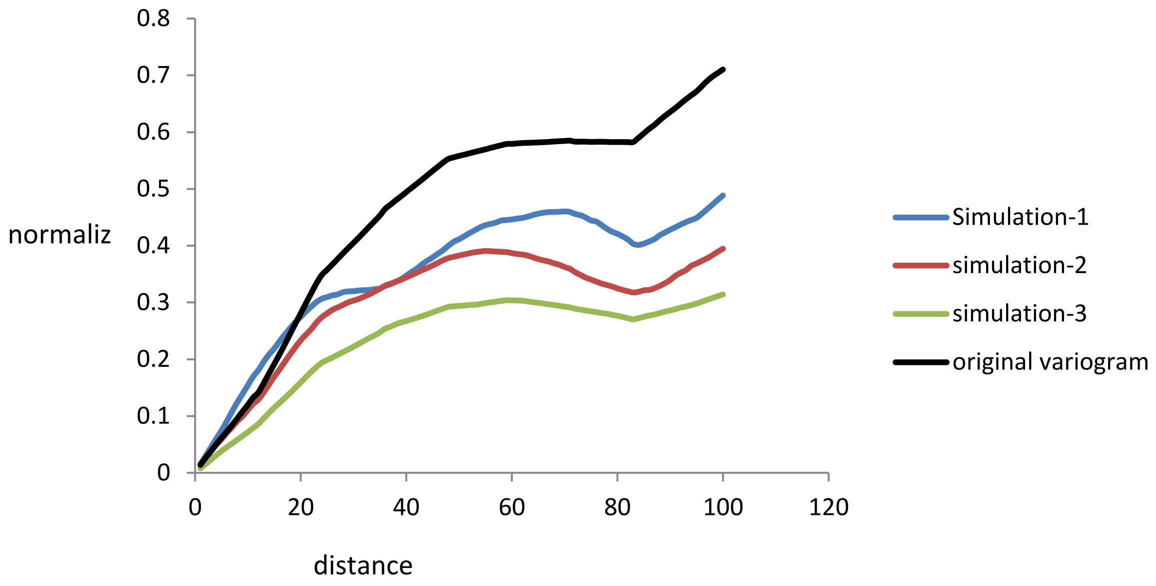


Fig:5.5- Experimental variogram of iron ore price

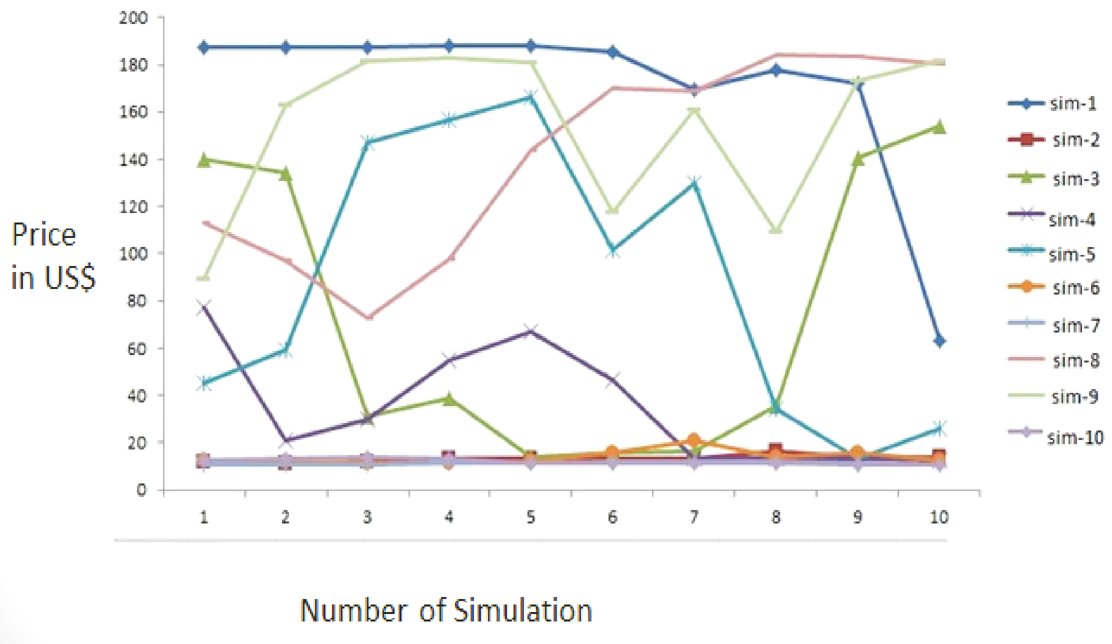


Fig:5.6- Predicted iron ore price for 10 years with 10 simulation for each year.

5.2.Production scheduling

Year wise production is obtained by following the procedure as described in methodology for stochastic model incorporating price uncertainty. The steps of pseudo code are followed and year wise production is obtained. Production scheduling is done for 10 years and year wise production chart and production schedules are shown in figure: 5.7 and table 5.2. The ultimate pit is obtained from the production schedules and is shown in fig: 5.8. From figure: 5.8 it is clear, that a smooth production scheduling is obtained for the entire life of mine with in the target range. From figure:5.8 it is observed that, a proper slope constraint of 45 degree is maintained and other constraints like reserve constraint also maintained since one ore block is extracted only once in total life of mine.

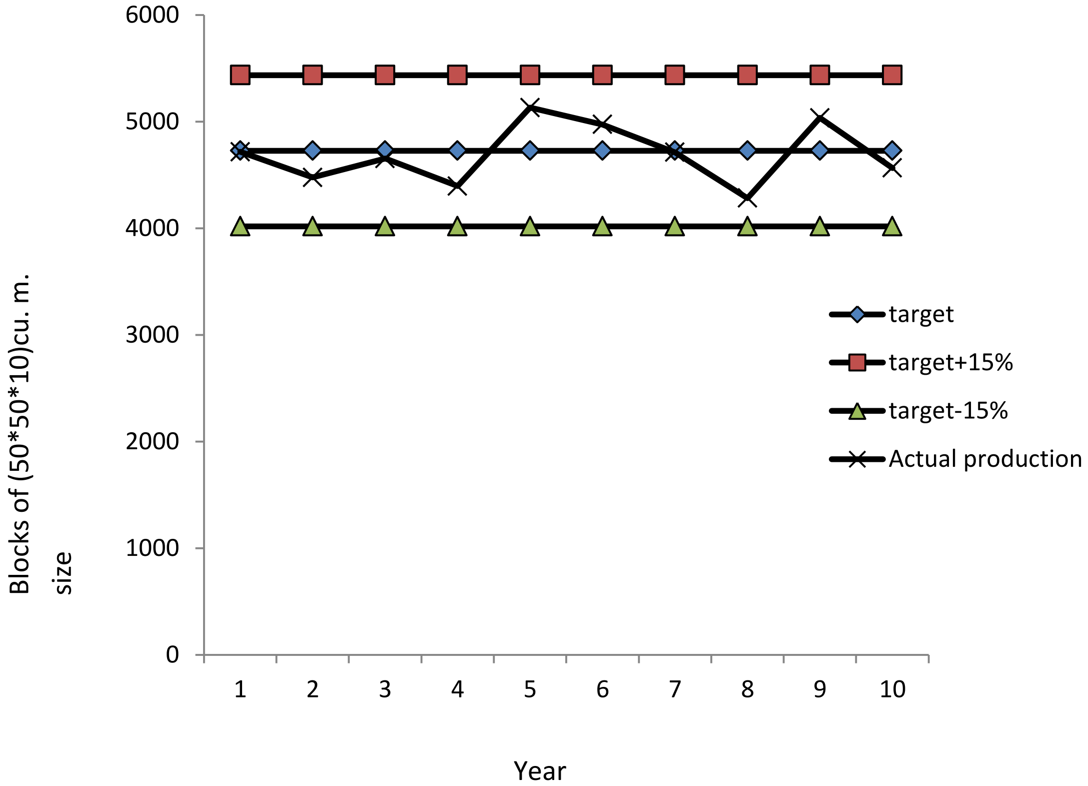


Figure-5.7: Production chart.

Blocks / Year	Expected number of blocks (50*50*10)cu.m size to get extracted	Number of blocks extracted by the proposed method	Difference (%)
1	4727.5	4716	0.24%
2	4727.5	4477	5.29%
3	4727.5	4654	1.55%
4	4727.5	4395	7.03%
5	4727.5	5131	8.53%
6	4727.5	4973	5.19%
7	4727.5	4712	0.32%
8	4727.5	4283	11.51%
9	42547.5	5035	6.50%
10	4727.5	4565	3.43%

Table: 5.2 – Production scheduling for different year along with percentage deviation from target

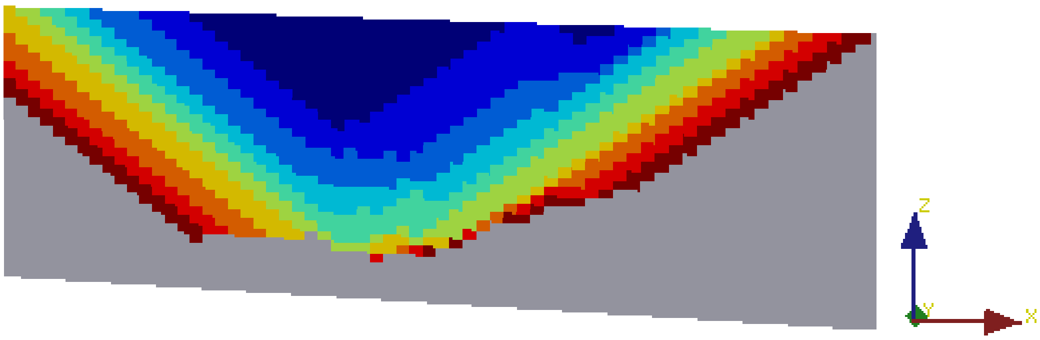


Fig-5.8 (a):- Ultimate pit in XY direction

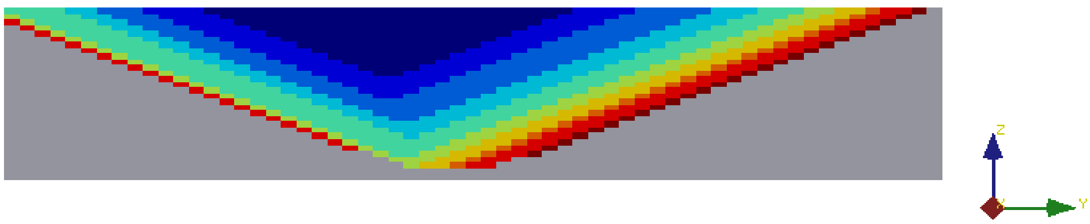
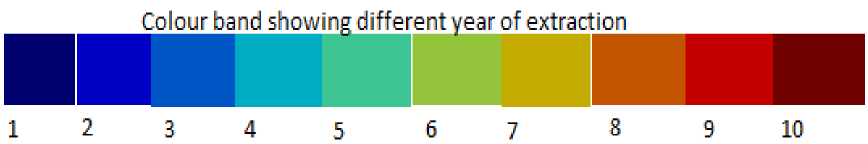


Fig: 5.8 (b)-Ultimate pit in YZ direction



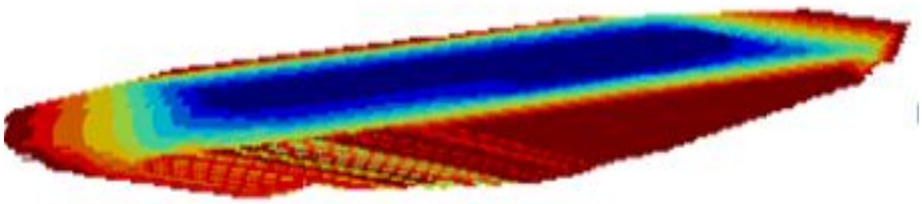


Fig-5.8 (c) 3-D view of pit

5.3.Net Present Value calculation

Net present value for each realization is calculated by subtracting the BEV of waste block from the respective ore block. The maximum, average and minimum net BEV of all simulations are obtained. NPV for all simulations are calculated. The cumulative NPV chart for stochastic model for the present case study is shown in fig: 5.9. From figure: 5.9, it can be concluded that the upside risk is higher than the downside risk of NPV.

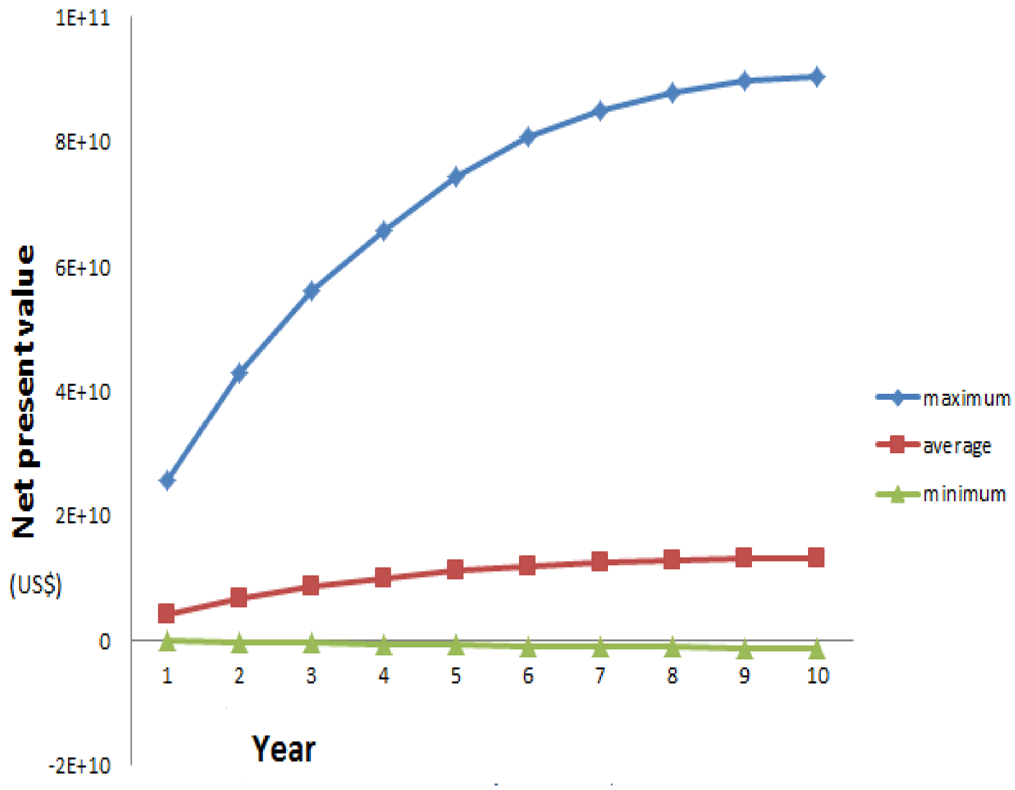


Fig-5.9: Net Present value chart

When this stochastic model is compared with a deterministic model where a fixed price (average of all simulated price value) is used for BEV calculation and production scheduling, the NPV chart can be shown in fig: 5.10.

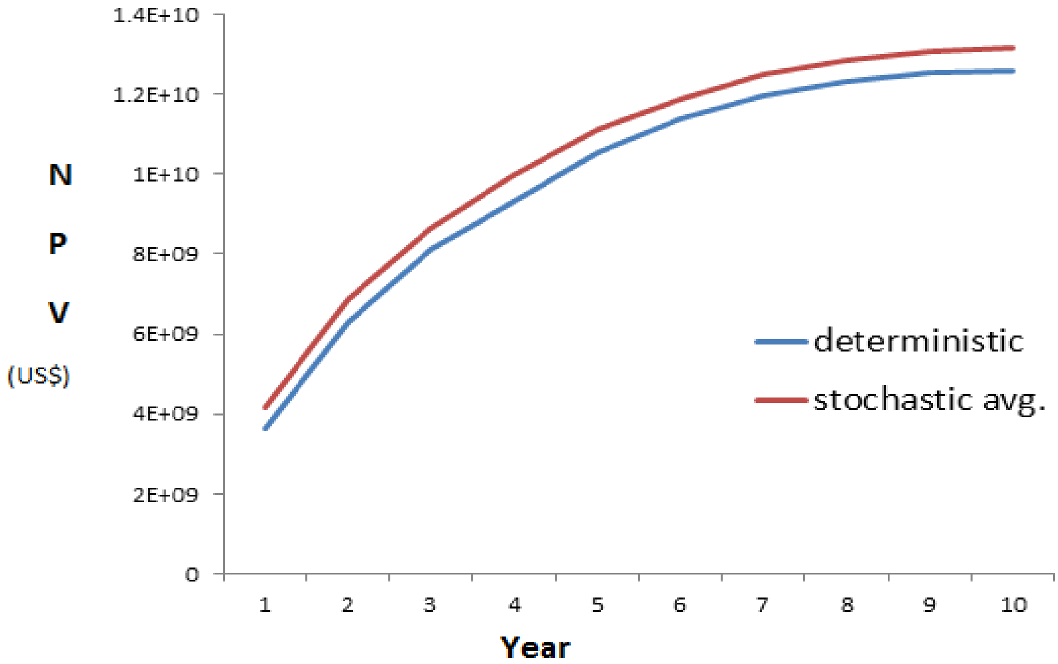


Fig: 5.10- NPV chart for both deterministic and for stochastic average

From figure:5.10 it can be concluded that, at the end of the mine life, the total net present value (NPV) generated from the SIP is $573 M higher than the NPV generated from a traditional deterministic model which is about 4.56% higher. This difference is due to economic discounting of the money and difference in production achieved in different year of production.

<u>CHAPTER -6</u>

CONCLUSSION

6. CONCLUSION

In this thesis, a new stochastic integer programming model is developed and applied to an Iron ore mine in India. The proposed stochastic integer programming uses a multiple conditionally simulated ore body model that is equi- probable representation of the actual deposit for optimizing annual production schedules in open pit mines. This approach accounts for the uncertainty in the metal selling price, unlike the traditional scheduling methods that are based on a single price which uses a single ore body model assumed to be actual deposit in the ground being mined.

The stochastic integer programming model is found out to be a powerful tool to manage the risk of not meeting the production target by controlling the magnitude and probability of risk within individual production period and, in addition controlling the risk and distributing it to between production periods. This model allows user to define the risk profile and generate the schedule with the optimum net present value (NPV) for the resultant risk profile. The risk profile in the schedules that are generated by traditional method is random and can lead to substantial losses, even premature closure of the mining operation, by failing to meet the production targets.

The proposed stochastic integer programming model is very efficient in the sense it needs only no extra binary variables than the traditional MIP formulation using single ore body model as input. The total number of binary variables representing the blocks for scheduling period in the stochastic integer programming formulation using many simulated ore body models is the same as in the MIP formulation using single ore body model.

On application of this proposed model to an Iron ore mine in India, it results in optimized production scheduling and resulted in 4.56% higher NPV than that of the deterministic approach.

CHAPTER -7

REFERENCES

7. REFERENCES

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